Adaptive Neuro-Fuzzy Inference System for Generating Scenarios in Business Strategic Planning

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Abstract—**The aim of this study is to investigate a new method for generating scenarios in order to cope with the data shortage and linguistic expression of an expert in scenario planning. This study incorporates the concepts of neural network and fuzzy logic. The proposed methodology includes: (1) defining the scope and internal and external variables (2) determining rules from experts (3) preparing ANFIS system and (4) generating probable scenarios based on training algorithm. Following this structure, it is possible to generate the feasible scenarios with their associated degree of probabilities. The applicability of the proposed method has been tested against a case study.**

I. INTRODUCTION

THE purpose of strategic planning is to guide an organisation to achieve its desired goals of the long-term development under the variation of environment [1]. Therefore, the future events play a key role in business strategic planning and managers need a mental model of future to make a better decision. Scenario planning is a very useful method for the estimation of future business conditions and, hence, the formulation of strategic business plans [2]. Various scenario planning approaches which can be found in the literature are classified into two major groups: qualitative and quantitative approaches.

SRI [3], Future Group [4], Global Business Network [4], and Schoemaker [5] methodologies are all subjective, qualitative in nature and firmly process-oriented approaches. It means that organisation learning process in these approaches is more important than the reliability of the content of the end product, which is the scenarios [6]. These approaches are not based on the past data but consider qualitative and subjective information of experts to construct scenarios. On the other hand, Godet [7-9] methodology which has been known as a quantitative methodology is essentially outcome-oriented. Quantitative methodology develops scenarios for particular phenomenon and sets key variables for a specific subject. The experts' rules in quantitative methodologies are dominant and they judge about the occurrence probability of each scenario. Quantitative methodologies such as Godet's framework consider the conditional probability of each occurrence which is assumed for different sets of environmental and organisational variables. In all scenario planning methodologies, experts' role is critical for decision making, and uncertain data always are the basis for developing future scenarios.

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In order to provide the most probable scenarios and cope with the issue of data shortage and linguistic expression of experts in scenario planning, the concepts of fuzzy logic and Artificial Neural Networks o have been applied in this paper. The goal of this research is to develop a scenario generation tool based on ANNs and fuzzy logic to eliminate the weakness of previous methodologies.

Section II will review the literature in the area of scenario generation tools. In section III, the details of Neuro-fuzzy framework for generating scenarios have been described. A case study is introduced in section IV. The findings of case study have been discussed in section V. In final section, the result of this research has been explained.

II. FUZZY LOGIC AND NEURAL NETWORKS IN SCENARIO PLANNING LITREATURE

There are some researches using fuzzy logic and ANNs in scenario planning. Khoo *et. al.* [10] developed a fuzzy management decision support system for scenario analysis. It is built on a hybrid technique: a combination of the fuzzy Delphi analysis and fuzzy reasoning technique. Wang [1] proposed a method of fuzzy scenario analysis to forecast the possible development in a strategic planning. This method considered the uncertainties involved in strategic planning to determine the compatible and possible scenarios. Li *et. al.* [2] developed a scenario generation tool by using theory of neural networks and theory of truth value flow inference. A rule-based five layer neural network was used for generating scenarios. A hybrid intelligent system was built up by Li [11] to develop marketing strategy. Fuzzy logic and ANNs were used to support marketing strategic decision making process. ANNs is designed to forecast market share and market growth, and fuzzy expert system model was developed to build the knowledge-based for making developing strategy. Royers and Royers [12] developed a framework to indicate how the fuzzy set approach may contribute to the evaluation and exploration of scenarios for strategic planning. A hybrid methodology will use 3 main modules: fuzzy sets, multicriteria analysis and case-based reasoning. As mentioned, developed methodologies rely on only one of the neural networks and fuzzy logic theories or using neural network as a tool for forecasting. Li [11] used both methods, fuzzy logic and ANNs but ANNs is utilized for forecasting, marketing growth and share and it is not applied as a tool that learns from experts and makes decision instead of them.

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The proposed methodology develops a hybrid intelligent framework by using fuzzy logic and ANNs theories. The main goals of this hybrid intelligent architecture will be:

- To improve the ability of managers to deal with uncertainty
- To present intelligent advice on business strategic planning
- To keep and use the experts' knowledge

To attain these objectives, there is a need for integration of fuzzy logic and ANNs. The theory of ANNs will be used to have an ability to learn and correct experts. Furthermore, fuzzy logic theory will be applied to deal with reasoning and using linguistic information acquired from experts. The next section will describe the proposed methodology.

III. SCENARIO GENERATION NEURO-FUZZY METHODOLOGY

This section will be related to design of a new intelligent methodology for generating scenarios. This methodology includes 4 steps which are explained as following:

A. Defining the scope and internal and external variables

The first step tries to analyse the problem and define the boundary of the system under examination. Understanding the main internal and external variables is the next step. Identifying variables, relationship between variables and defining key variables are the main objectives of this step. This research recommends Godet's method [7] in defining the key variables.

B. Determining rules from experts

In this step, the knowledge of expert should be gathered and summarised in the form of rules for using in the next step.

C. Preparing ANFIS system

This system proposes a hybrid system to generate scenarios by using fuzzy logic and neural networks. Jang [13, 14] presented a framework called Adaptive Neuro-Fuzzy Inference System (ANFIS) which is used in this paper. ANFIS follows the typical Sugeno fuzzy rule:

IF x_1 is A_1

AND x_2 is A_2

…

AND x_m is A_m

THEN $Y = f(x_1, x_2, \ldots, x_m)$

Where x_1, x_2, …, x_m are input variables; A_1, A_2, …, A_m are fuzzy sets; and Y is either a constant or a linear function of the input variables. When Y is a constant, we obtain a zero-order Sugeno fuzzy model [15].

ANFIS architecture contains a 6-layer forward pass ANNs as shown in Figure 1. The output and input of each layer has been presented as following:

y_i^k = Output of neuron i in layer k

x_i^k = Input of neuron i in layer k

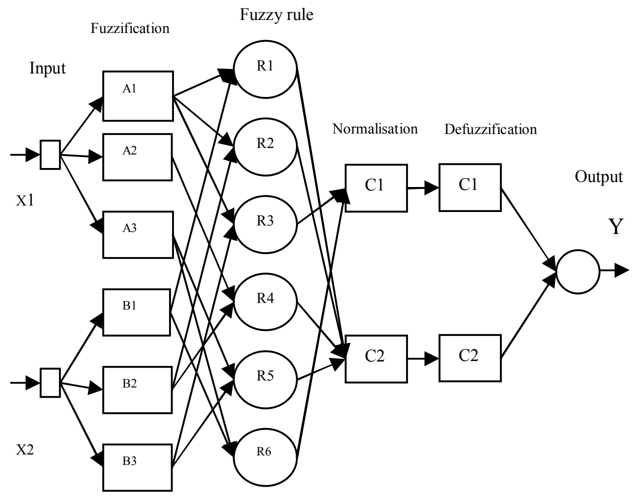

Fig. 1. Adaptive Neuro-Fuzzy inference system (ANFIS)

Layer 1 is the input layer. The neurons in this layer transmit external crisp signals directly to the next layer. That is,

$$y_i^1 = x_i^1 \tag{1}$$

Layer 2 is the fuzzification layer. Neurons receive a crisp input and identify the degree of neurons' fuzzy sets. Based on Jang's model, membership function of fuzzification neurons is a bell activation function which is specified as [14, 15]:

$$y_i^2 = \frac{1}{1+\left(\frac{x_i^2 - a_i}{c_i}\right)^{2b_i}} \tag{2}$$

a_i, b_i and c_i are parameters that control respectively, the centre, width and slope of the bell activation function of neuron i.

Layer 3 is the fuzzy rule layer. The inputs of fuzzy rule neuron come from the fuzzification neuron. For example, neuron $R1$ receives inputs from neurons $A1$ and $B1$. The conjunction of the rule antecedents is evaluated by the fuzzy operation intersection and implemented by the product operator [15].

$$y_i^3 = \prod_{j=1}^{k} x_{ji}^{(3)} = \mu_i \tag{3}$$

$x_{ji}^{(3)}$ are the inputs and y_i^3 is the output of the rule neuron i in layer 3. μ_i represents the firing strength or the truth value of Rule i [14].

Layer 4 is the normalisation layer. Neurons receive inputs from fuzzy rule neuron and normalised firing strength of a given rule. The output of neuron i in layer 4 is determined as,

$$y_i^4 = \frac{x_{ii}}{\sum_{j=1}^{n} x_{ji}} = \frac{\mu_i}{\sum_{j=1}^{k} \mu_j} = \bar{\mu}_i \quad (4)$$

Layer 5 is defuzzification layer. Each neuron in this layer is connected to the respective normalisation neuron, and also receives initial inputs [15].

$$y_i^5 = x_i^5 * f_i = \bar{\mu}_i * f_i \quad (5)$$

Layer 6 is a summation neuron which calculates the sum of all defuzzification neurons as following:

$$y = \sum_{i=1}^{n} x_i^6 = \sum_{i=1}^{n} \bar{\mu}_i * f_i \quad (6)$$

D. Generating probable scenarios based on training algorithm

In the ANFIS training algorithm, each epoch is composed of a forward and a backward pass [15]. In the forward pass, outputs are based on the layer by layer calculation and rule consequent parameters are determined by the least-squares estimators. P linear equations can be formed in terms of the consequent parameters as:

$$\begin{cases} y_d(1) = \bar{\mu}_1(1) f_1(1) + \bar{\mu}_2(1) f_2(1) + \ldots + \bar{\mu}_n(1) f_n(1) \\ y_d(2) = \bar{\mu}_1(2) f_1(2) + \bar{\mu}_2(2) f_2(2) + \ldots + \bar{\mu}_n(2) f_n(2) \\ \ldots \\ y_d(P) = \bar{\mu}_1(P) f_1(P) + \bar{\mu}_2(P) f_2(P) + \ldots + \bar{\mu}_n(P) f_n(P) \end{cases}$$

Where P, n are the number of input-output training sets and neurons in the rule layer respectively. In matrix notation, y_d can be shown as:

$$y_d = \text{AK} \quad (7)$$

Where y_d is a $P \times 1$ desired output vector,

$$y_d = \begin{bmatrix} y_d(1) \\ y_d(2) \\ \ldots \\ y_d(P) \end{bmatrix}$$

A is a $P \times (n \times (1+m))$ matrix where m is the number of input variables:

$$\begin{bmatrix} \bar{\mu}_1(1) & \bar{\mu}_1(1)\,x_1(1) & \cdots & \bar{\mu}_1(1)\,x_m(1) & \cdots \bar{\mu}_n(1) & \bar{\mu}_n(1)\,x_1(1) & \cdots & \bar{\mu}_n(1)\,x_m(1) \\ \bar{\mu}_1(2) & \bar{\mu}_1(2)\,x_1(2) & \cdots & \bar{\mu}_1(2)\,x_m(2) & \cdots \bar{\mu}_n(2) & \bar{\mu}_n(2)\,x_1(2) & \cdots & \bar{\mu}_n(2)\,x_m(2) \\ \ldots & \ldots & \cdots & \ldots & \cdots \ldots & \ldots & \cdots & \ldots \\ \bar{\mu}_1(P) & \bar{\mu}_1(P)\,x_1(P) & \cdots & \bar{\mu}_1(P)\,x_m(P) & \cdots \bar{\mu}_n(P) & \bar{\mu}_n(P)\,x_1(P) & \cdots & \bar{\mu}_n(P)\,x_m(P) \end{bmatrix}$$

and K is an $(n \times (m+1)) \times 1$ vector of unknown consequent parameters,

$$k = [k_{10} \quad k_{11} \quad k_{12} \quad \ldots \quad k_{1m} \quad \ldots \quad k_{n0} \quad k_{n1} \quad k_{n2} \quad \ldots \quad k_{nm}]^T$$

In the forward pass, a least square estimate of k, k^*, minimises the squared error $\|Ak - y_d\|^2$ which is done by using the pseudo inverse technique [15]:

$$K^* = (A^T A)^{-1} A^T y_d \quad (8)$$

$$y = A \times K^* \quad (9)$$

Where A^T is the transpose of A, and $(A^T A)^{-1} A^T$ is the pseudo inverse of A if $A^T A$ is non-singular. The error vector can be computed by actual network output vector (y) and

$$e = y_d - y \quad (10)$$

The backward pass applies the back-propagation algorithm. For instance, a correction of parameter a of the bell activation function is as following:

$$\Delta a = -\alpha \frac{\partial E}{\partial a}$$

$$= -\alpha \frac{\partial E}{\partial e} * \frac{\partial e}{\partial y} * \frac{\partial y}{\partial(\bar{\mu}_i f_i)} * \frac{\partial(\bar{\mu}_i f_i)}{\partial \bar{\mu}_i} * \frac{\partial \bar{\mu}_i}{\partial \mu_i} * \frac{\partial \mu_i}{\partial \mu A1} * \frac{\partial \mu A1}{\alpha a} \quad (11)$$

Where α is the learning rate and E is the instantaneous value of the squared error:

$$E = \frac{1}{2} e^2 = \frac{1}{2} (y_d - y)^2 \quad (12)$$

Thus:

$$\Delta a = -\alpha (y_d - y)(-1) f_i * \frac{\bar{\mu}_2 (1 - \bar{\mu}_2)}{\mu_2} * \frac{\mu_i}{\mu_{A1}} * \frac{\partial \mu_{A1}}{\partial a} \quad (13)$$

Where

$$\frac{\partial \mu_{A1}}{\partial a} = -\frac{1}{\left[1 + \left(\frac{x1 - a}{c}\right)^{2b}\right]^2} * \frac{1}{c^{2b}} * 2b * (x1 - a)^{2b-1} * (-1)$$

$$= \mu_{A1}^2 * \frac{2b}{c} * \left(\frac{x1 - a}{c}\right)^{2b-1}$$

Similarly, parameters b and c can be corrected through this approach. In the hybrid learning algorithm, there are several ways of combining gradient descent and least square method [13]. This method can be varied based on the required performance level and available computing resources, for instance, there is an opportunity for better performance in ANFIS system by updating membership function.

IV. CASE STUDY

This section shows the result of using ANFIS in generating scenarios. A virtual case study used to show the details of scenario generation tools. In this case study, different strategic options are based on the two variables: market share and suppliers. Table 1 shows the rules developed for this case study.

Table1. Fuzzy rules of ANFIS

Market share (X1)	Relationship with suppliers (X2)	Strategic options (D)	success probability (P)
Good	Bad	D1	0.7
	Average	D2	0.6
	Good	D3	0.9
Average	Bad	D4	0.65
	Average	D5	0.3
	Good	D6	0.8
Bad	Bad	D7	0.8
	Average	D8	0.6
	Good	D9	0.8

In this case study, the success probability for a specific strategy is considered as an objective function, designated as Y in ANFIS rules. If Y is not a function of input variables, zero order Sugeno fuzzy model should be used [15]. In this circumstance, there is no forward pass for training algorithm because $A^T A$ is singular and it is not possible to account for the pseudo inverse of A.

Table 2 presents the training and checking data. It contains the information about the strategic option and accumulated probability for a specific market share and relationship with supplier. Accumulated probability means the summation of probabilities for each condition of market share (good, average, bad) and relationship with suppliers (good, average, bad). When training data is small, the membership functions should be kept fixed through the learning process [14].

Table2. training and checking data

Row	Market Share (X1)	Relationship with suppliers (X2)	Strategic option	Accumulated Probability
Training Data				
T1	-1	20	D9	0.2
T2	0.6	28	D1	0.25
T3	0.4	22	D8	0.4
T4	0.5	27	D4	0.55
Checking Data				
C1	-0.9	20	D9	0.3
C2	0.6	27	D4	0.35
C3	0.4	23	D8	0.5
C4	0.4	27	D5	0.65

As mentioned, ANFIS method was used to generate new fuzzy membership function for generating scenarios. There are 9 fuzzy rules and the number of epochs is 300. Learning rate and acceptance error are set to 0.02 and 0.005 respectively. At the end of 300 training periods, the network error convergence curve can be derived as shown in figure 2. There are the decreasing trend for the errors of training and checking data. Figures 3 and 4 illustrate the initial and final membership function of input data (supplier relationship and market share).

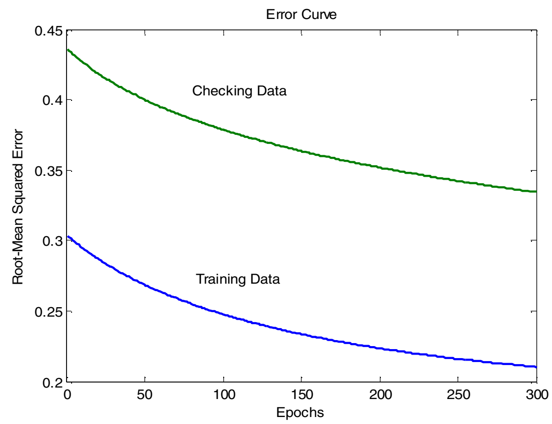

Fig. 2. The curve of network error convergence

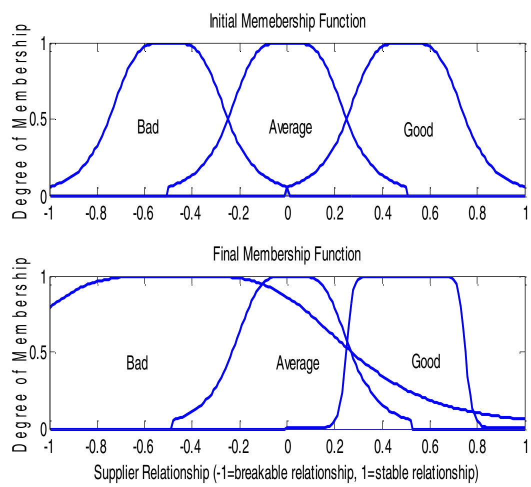

Fig. 3. Membership function of the supplier relationship

modifies the final membership function of the supplier relationship especially "Bad" curve as shown in Figure 5.

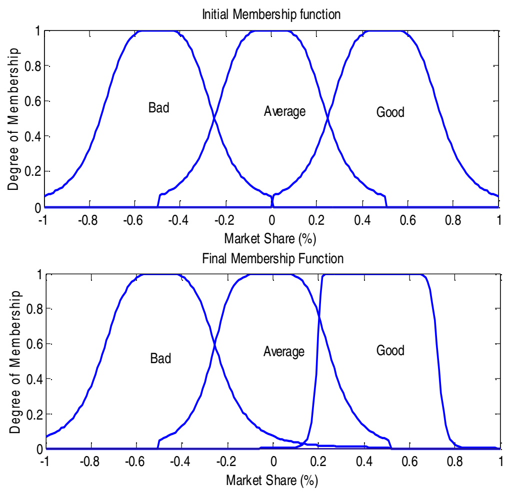

Fig. 4. Membership function of the Market Share

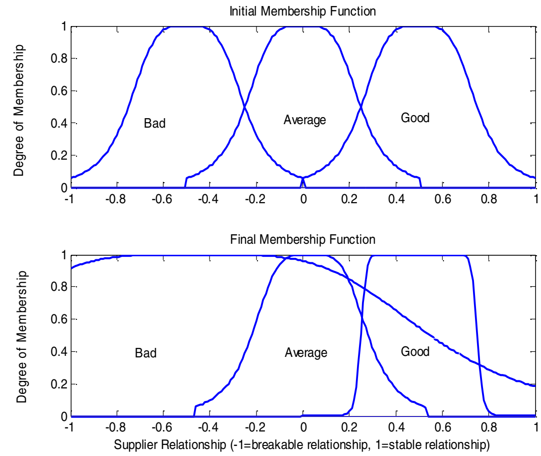

Fig. 5. Membership function of the supplier relationship

After training algorithm, the system has the ability to identify the strategic option and also calculate the success probability for specific input data according to the final membership function. For example, if the market share and the supplier relationship estimate 23.5% and -0.1 accordingly, D4 strategic option is predicted to be recommended and success probability will predict 15.00%.

Training data plays a critical role in this methodology. For instance, if the success probability of the first training data is increased by 6%, D1 strategic option with success probability of 15.95% will be suggested. Table 3 shows the changes in the recommended strategic options and occurrence probability when uncertainties are introduced into the training data. As can be seen in Table 3, this particular input data are sensitive to first training data and the changes in the probability of training data leads to changes in the strategic options. It also affects on the final membership function for other training data.

Table3. The result of sensitivity analysis on probability of training data

Training Data	Probability	Strategic Option	New Probability	New Strategic Option
T1	0.2	D4	0.26	D1
T1	0.2	D4	0.14	D4
T2	0.25	D4	0.3	D4
T2	0.25	D4	0.2	D4
T3	0.4	D4	0.45	D4
T3	0.4	D4	0.35	D4
T4	0.55	D4	0.5	D4
T4	0.55	D4	0.6	D4

Another sensitivity analysis can be performed by introducing uncertainty into X1 or X2 of each training data. If the market share(X1) of T1 is shifted from 20 to 20.5, the new strategic option will be D1 instead of D4. Furthermore, it

V. Discussion

The membership functions associated with market share and supplier relationship indicate the experts' views about the future event. Some of the training data were arbitrarily varied to show the importance of sensitivity analysis and the effects of uncertainties after selecting a strategic option. From the result, it can be inferred that the strategic option is changed if the probability of one rule changes only 6% or the market share modified by 0.5%. Obviously, sensitivity analysis shows that organisation should not rely on only one strategic option. Because of the high level of uncertainty in future, there is a need that organisations have some alternatives for a chosen strategic option. Although scenario generation software advises a specific strategic option but it is required to investigate other alternative strategic options due to the existence of uncertainties.

VI. Conclusion

An ANFIS system has been developed for generating scenarios. It is built based on a hybrid technique: a combination of ANNs and fuzzy logic. Hybrid architecture is the central point of the proposed methodology which allows having fuzzy rules and learning algorithm in scenario generation. ANNs brings out the ability to learn from experts. Fuzzy logic gives a consensus to express the ambiguity in human thinking and is able to mimic the human reasoning process. The developed methodology has the ability to learn and correct experts and also translate the linguistic experts' rules. This methodology is a combination of qualitative and quantitative techniques in generating scenarios by using ANNs as a learning tool which is the main goal of qualitative approaches in scenario planning and also fuzzification and defuzzification layers which help to work with quantification data. In this paper, a case study is also presented to demonstrate how the hybrid intelligence scenario generator works. The result of the case study shows that the degree of uncertainty in scenario planning greatly affects on the selection of strategic options.

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